THE VALIDITY OF REAL-TIME DATA GENERATED BY A WEARABLE MICROTECHNOLOGY DEVICE.

ABSTRACT

The purpose of this study was to investigate the validity of global positioning system (GPS) and micro-electrical-mechanical-system (MEMS) data generated in real-time via a dedicated receiver. Post-session data acted as criterion as it is used to plan the volume and intensity of future training and is downloaded directly from the device. 25 professional rugby league players completed two training sessions wearing a MEMS device (Catapult S5, firmware version: 2.27). During sessions, real-time data was collected via the manufacturer receiver and dedicated software (Openfield v1.14) which was positioned outdoors at the same location for every session. GPS variables included total-, low- (0 to 3 $m \cdot s^{-1}$), moderate- (3.1 to 5 $m \cdot s^{-1}$), high- (5.1 to 7 $m \cdot s^{-1}$) and very-high-speed (> 7.1 $m \cdot s^{-1}$) distances. MEMS data included total session PlayerLoad™. When compared to post-session data, mean bias for total-, low-, moderate-, high- and very-high-speed distances were all *trivial*, with the typical error of the estimate (TEE) *small, small, trivial, trivial* and *small* respectively. Pearson correlation coefficients for total-, low-, moderate-, high- and very-high-speed distances were *nearly perfect*, *nearly perfect*, *perfect*, *perfect* and *nearly perfect* respectively. For PlayerLoad™, mean bias was *trivial* whilst TEE was *moderate* and correlation *nearly perfect*. Practitioners should be confident that when interpreting real-time speed-derived metrics, the data generated in real-time is comparable to that downloaded directly from the device post-session. However, practitioners should refrain from interpreting accelerometer derived data (i.e. PlayerLoad™) or acknowledge the *moderate* error associated with this real-time measure.

KEY WORDS: global positioning systems, accelerometers, PlayerLoad™, training load

INTRODUCTION

Quantifying the training and competition loads placed upon team sport players is an important process to promote adaptations and manage negative outcomes (e.g. injury).[4,6] Global positioning systems (GPS) and micro-electrical-mechanical-systems (MEMS) are now commonly utilised to measure the external loads (e.g., walking, running, sprinting distances) accrued by athletes.[10] Strength and conditioning coaches 'download' this data directly from the device (i.e. *post-session* data) to calculate training loads over longitudinal periods (e.g. 28- and 7-day averages of training load [i.e. acute:chronic workload ratio]) to inform the planning of both the volume and intensity of future field-based training sessions.[4] Since the initiation of GPS and MEMS data within team-sports, microtechnology companies have provided the capability to monitor these loads in *real-time* via a dedicated receiver (Figure 1) to increase the control of training prescription.[2] For example, if a strength and conditioning coach identified a need to limit the amount of high-speed-running during the session on that day, it is perceived that this can then be accurately controlled in *real-time* as players complete the session.

Although both derived from GPS and MEMS, *real-time* data arrives at the end-user differently, via a specific receiver, whereas *post-session* data is downloaded directly from the device. Therefore, at present, practitioners should not assume that the data they receive in *real-time* during the session is comparable to that which they use to inform the planning of training (e.g. *post-session* data). As the volume and intensity targets for each player are underpinned by longitudinal analyses conducted using *post-session* data and subsequently controlled in *real-time*[7], understanding the agreement between *real-time* and *post-training* data is an important consideration. However, despite the exponential increase in research relating to the validity and reliability of GPS and MEMS devices to quantify distance and speed variables specifically[9], only a single study (conducted in 2010), has investigated this aspect of training load monitoring.[1] By comparing the signal (smallest meaningful difference [SMD]) to the noise (typical error [TE]) of *real-time* to *post-session* data, Aughey and Falloon (2010)[1] found that whilst the signal exceeded the noise (SMD = 134.6 m; TE = 55.8 m) for total distance, this was reduced considerably during jogging (4.2 to 5.0 $m \cdot s^{-1}$; SMD = 33.5 m; TE = 30.1 m) and running (5.0 to 6.9 $m \cdot s^{-1}$; SMD = 31.9 m; TE = 31.3 m). In particular, the noise exceeded the signal during *real-time* collection for sprinting (SMD = 17.3 m; TE = 23.7 m). The above findings showed that only total distance demonstrated an acceptable signal:noise ratio, suggesting that *real-time* data possesses limited validity and applicability to practice. However, despite the previous findings, developments in MEMS, its associated software and the increased number of variables available during *real-time* analysis, mean a reinvestigation is warranted.[7] Strength and conditioning coaches who use microtechnology devices in *real-time* require confidence that this data is comparable to that which is used to conduct detailed analyses of the accumulation and distribution of training load. Therefore, the aim of the current study was to re-establish the validity of *real-time* MEMS data compared to *post-session* data derived from a commonly used software platform (Catapult Openfield).

METHODS

Experimental Approach to the Problem

An observational research design was conducted in which the participants completed 2 training sessions whilst wearing a GPS and MEMS device on the same artificial pitch and at the same time of day with environmental conditions clear for both testing sessions (mean temperature: 6 ± 1^{o}C; relative humidity: 88 ± 2%). The training sessions were focused on enhancing the squads technical and tactical capabilities (i.e. skills based training) during the initial stages of the 2017 competitive season. The lead researcher was not involved in the prescription of training content relating to the sessions. *Real-time* GPS and MEMs data was generated during each session and compared to that downloaded directly from the device *post-session*. Therefore, players provided 40 session observations in total comprising of both *real-time* and *post-session* data per observation. The lead researcher was experienced (> 5 years) in operating the microtechnology system and players possessed full familiarisation with the devices as part of their regular monitoring practices (i.e. > 3 seasons).

Subjects

Twenty male professional rugby league players (age: 27.0 ± 5.0; height: 184.3 ± 6.9 cm; weight: 94.4 ± 11.7 kg) from one European Super League club participated in the current study. Ethics approval was gained by the universities Institutional Review Board conforming to the spirit of the Helsinki declaration and written informed consent was gained from all participants following information of the benefits and risks of the investigation.

Procedures

During all sessions, players wore a GPS and MEMS device (Optimeye S5, Catapult Innovations, Scoresby, Victoria) which included 10 Hz GPS, 100-Hz tri-axial accelerometer, gyroscope and magnetometer (firmware version 2.27; Figure 1). This positioned between the scapulae within a manufacturer designed vest and operated by the lead researcher according to typical procedures.[7] 10 Hz GPS has been reported to be valid and reliable for quantifying *post-session* distance and speed measurements.[7] The mean number of satellites and horizontal dilution of precision (HDOP) during data collection was 14 ± 1 and 0.6 ± 0.2 respectively. During each training session, the *real-time* receiver (2.4 GHz radio frequency; firmware version 2.27; Figure 1) was connected to a laptop (Dell XPS; Windows 10 Pro (x64); Intel Core i7; 2.6 GHz; 16 GB random access memory) via universal serial bus (USB) which collected the *real-time* variables through Catapult Openfield software (v1.14, Catapult

Innovatons, Scoresby, Victoria). This was positioned outdoors on a grass pitch at the same location for every training session, positioned 5 metres away from the 'in-goal' line so that at any time during the session, players were within 5 to 105 metres of the receiver. This distance falls within manufacturer recommended radius of 150 metres (personal communication with manufacturers). During each session, periods of training were 'clipped' in *real-time* so that no data recorded for analysis included scheduled periods of no activity (i.e. drinks breaks). These periods were automatically synchronised between *real-time* and *post-training* conditions within the software.

***** INSERT FIGURE 1 HERE*****

The total distance (m) covered during a training session was compared for *real-time* and *post-training* within arbitrarily demarcated speed zones. This included low- (0 to 3 $m \cdot s^{-1}$), moderate- (3.1 to 5 $m \cdot s^{-1}$), high- (5.1 to 7 $m \cdot s^{-1}$) and very-high-speed-distances (> 7.1 $m \cdot s^{-1}$). Derived from the tri-axial accelerometer, the total PlayerLoad™ accumulated in each training session was compared between *real-time* and *post-training* conditions. PlayerLoad™ is a modified vector magnitude which aims to encapsulate all velocity, acceleration, change of direction and collision demands experienced by players.[3] It is expressed as the square root of the sum of the squared instantaneous rate of change in acceleration in each of the three vectors (X: mediolateral, Y: anterio-posterior, and Z: vertical) divided by 100 and expressed in arbitrary units (AU).[2,3]

STATISTICAL ANALYSES

Based on 90% confidence limits (90% CL), the agreement between the criterion measure (*post-session* data for each variable) and the practical measures (*real-time* data for each variable) were assessed using an excel spreadsheet[5] to calculate the mean bias, typical error of the estimate (TEE) and Pearson correlation coefficient. The standardised mean bias was rated as *trivial* (< 0.19), *small* (0.2 to 0.59), *medium* (0.6 to 1.19) or *large* (1.2 to 1.99).[5] The standardised TEE was rated as *trivial* (< 0.1), *small* (0.1 to 0.29), *moderate* (0.3 to 0.59) or *large* (> 0.59).[5] Correlation coefficient magnitudes were rated as *trivial* (0 to 0.09), *small* (0.1 to 0.29), *moderate* (0.3 to 0.49), *large* (0.5 to 0.69), *very large* (0.7 to 0.89), *nearly perfect* (0.9 to 0.99) and *perfect* (> 0.99).[5]

RESULTS

The mean duration of the sessions were 50.3 ± 2.6 mins. Table 1 highlights the mean ± standard deviation of the external loads (PlayerLoad™ [AU], total-, low-, moderate-, high- and very-high-speed distances [m]) plus the standardised mean bias, TEE and Pearson correlation coefficients all with 90% CL for *real-time* and *post-session* conditions.

**** INSERT TABLE 1 HERE****

The regression equation to estimate *post-session* data from *real-time* data for each variable is:

$$Y = \text{intercept} + (\text{slope} \times X)$$

Where Y is the estimated *post-session* data for a given variable and X is the *real-time* data for a given variable.

The regression equations for each variable are:

Total-Distance:

$$Y = -467.601 + (1.152 \times X)$$

Low-Speed Distance (0 to 3 $m{\cdot}s^{-1}$):

$$Y = -545.544 + (1.246 \times X)$$

Moderate-Speed Distance (3 to 5 $m \cdot s^{-1}$):

$$Y = -5.814 + (0.998 \text{ x } X)$$

High-Speed Distance (5 to 7 $m \cdot s^{-1}$):

$$Y = -1.959 + (0.948 \text{ x } X)$$

Very-High-Speed Distance (> 7 $m \cdot s^{-1}$):

$$Y = 0.528 + (0.804 \text{ x } X)$$

PlayerLoad™:

$$Y = 27.899 + (0.922 \text{ x } X)$$

DISCUSSION

This study assessed the agreement between GPS and MEMS data derived by either *real-time* or *post-session* (criterion) methods in professional rugby league players. The findings suggest that *real-time* speed-derived variables determined from 10Hz GPS (Optimeye S5, Catapult Innovations, Scoresby, Victoria) can provide valid quantification of the external loads accrued by players when compared to data downloaded directly from the device. However, practitioners should be cautious of interpreting real-time accelerometer derived data.

For strength and conditioning coaches working with team-sport players, controlling and developing their high-speed running exposure has been suggested to be an important process to reduce negative training outcomes such as injury.[8] Given the *trivial* error between *real-time* and *post-session data*, the findings of the current study suggest that practitioners should be confident of making decisions in *real-time* regarding the accumulation of a players high-speed (5 to 7 $m \cdot s^{-1}$) distance. However, they should acknowledge the *small* error between *post-session* and *real-time* when quantifying very-high-speed (> 7.1 $m \cdot s^{-1}$) running exposure. The current findings somewhat support earlier research[1] using previous models of the microtechnology device (MinimaxXX, Team Sport 2.0, Catapult Innovations) which report poorer agreement for very-high-speed running (i.e. > 7 $m \cdot s^{-1}$) compared to lower speeds, although in the current study very-high-speed running was still found to possess acceptable error.

For collision-based team-sports (e.g. rugby league, American football), quantifying collision- and accelerative-based activity during training and competition is an important aspect[3] and therefore, monitoring accelerometer derived measures in *real-time* is an attractive capability for practitioners. However, whilst *post-session* PlayerLoad™ data has been found to be both reliable and valid[2], in *real-time, moderate* errors were found when compared to the data downloaded directly from the device. It is unknown why *real-time* PlayerLoad™ data demonstrated greater errors compared to speed-derived methods. It is possible that differences in how the *real-time* receiver receives data from the 100Hz tri-axial accelerometer compared to 10Hz GPS can explain the greater errors associated with *real-time* PlayerLoad™. Therefore, practitioners should ideally refrain from interpreting *real-time* PlayerLoad™ during training and competition but should they wish to estimate *post-session* from *real-time* data, the regression equations provided in the current study can be used whilst acknowledging the error associated with this.

PRACTICAL APPLICATIONS

Practitioners can be confident in making decisions of the training load imposed using data that calculates the *real-time* distance covered in low- (0 to 3 $m \cdot s^{-1}$) to high-speed (5.1 to 7 $m \cdot s^{-1}$) thresholds derived from the Catapult S5 microtechnology device. However, practitioners should focus on speed-derived methods given the errors associated with *real-time* tri-axial accelerometer data.

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Figure 1. Image of the wearable microtechnology device (Optimeye S5, Catapult Innovations, Scoresby, Victoria) and the *real-time* receiver positioned on a tri-pod with universal serial bus attachment.

Table 1. Comparison of real-time and post-session GPS and MEMS data including standardised mean bias, typical error of estimate (TEE) and Pearson correlation coefficient, all with 90% confidence limits.

	Total Distance	**Low-Speed (0 to 3 $m \cdot s^{-1}$)**	**Moderate-Speed (3 to 5 $m \cdot s^{-1}$)**	**High-Speed (5 to 7 $m \cdot s^{-1}$)**	**Very-High-Speed (> 7 $m \cdot s^{-1}$)**	**PlayerLoad™ (AU)**
Descriptive Data (mean ± SD)						
Real-Time	3266.7 ± 303.7 m	2325.1 ± 268.6 m	693.6 ± 110.1 m	200.4 ± 99.5 m	29.6 ± 37.5 m	304.7 ± 34.2 AU
Post-Session	3294.7 ± 358.2 m	2351.0 ± 339.4 m	686.3 ± 110.2 m	188.1 ± 94.6 m	24.3 ± 31.0 m	308.9 ± 34.0 AU
Validity Analysis						
Standardised Mean Bias	-0.08 [-0.14 to -0.01]	-0.08 [-0.14 to -0.01]	0.07 [0.05 to 0.09]	0.13 [0.11 to 0.16]	0.17 [0.08 to 0.26]	-0.12 [-0.22 to -0.02]
	Trivial	*Trivial*	*Trivial*	*Trivial*	*Trivial*	*Trivial*
Standardised TEE	0.22 [0.18 to 0.27]	0.17 [0.14 to 0.21]	0.08 [0.07 to 0.10]	0.08 [0.07 to 0.10]	0.24 [0.20 to 0.29]	0.38 [0.32 to 0.46]
	Small	*Small*	*Trivial*	*Trivial*	*Small*	*Moderate*
Correlation	0.98 [0.96 to 0.99]	0.99 [0.98 to 0.99]	1.00 [0.99 to 1.00]	1.00 [0.99 to 1.00]	0.97 [0.95 to 0.98]	0.93 [0.88 to 0.96]
	Nearly Perfect	*Nearly Perfect*	*Perfect*	*Perfect*	*Nearly Perfect*	*Nearly Perfect*